Bayesian Anomaly Detection for Ia Supernovae using JAX-bandflux

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Robust parameter estimation for Type Ia supernovae is crucial for precision cosmology. Anomalous data points from instrumental artifacts or astrophysical contamination can bias SALT3 fits and propagate into cosmological parameters. We present a differentiable Bayesian framework that simultaneously fits supernova light curves while identifying anomalous observations, implemented in JAX for GPU acceleration.

Bayesian Anomaly Detection

Problems with current methods:

- Traditional methods are not model aware
- Anomalies sought before/after fitting, not simultaneously
- Binary classification (no encoding of belief)
- Standard likelihoods cannot incorporate anomalous data

Our solution

We model each data point as either expected or anomalous:

1. **Define anomaly mask:** $\varepsilon_i \in \{0, 1\}$ for each data point
2. **Bernoulli prior:** $P(\varepsilon_i) = p^{\varepsilon_i}(1-p)^{(1-\varepsilon_i)}$
3. **Piecewise likelihood:**

$$P(\vec{D}, \vec{\epsilon}|\theta) = \prod_{i=1}^{N} \left(L_i(\theta)(1-p)\right)^{(1-\epsilon_i)} \left(\frac{p}{\Delta}\right)^{\epsilon_i}$$

4. **Marginalize over** ϵ: $P(\mathcal{D}|\theta) = \sum_{\varepsilon \in \{0,1\}^N} P(\mathcal{D}, \varepsilon|\theta)$
5. **Dominant mask approximation:**

$$P(\mathcal{D}|\theta, \varepsilon_{\max}) \gg \max_j P(\mathcal{D}|\theta, \varepsilon^{(j)})$$

6. **Final log-likelihood:**

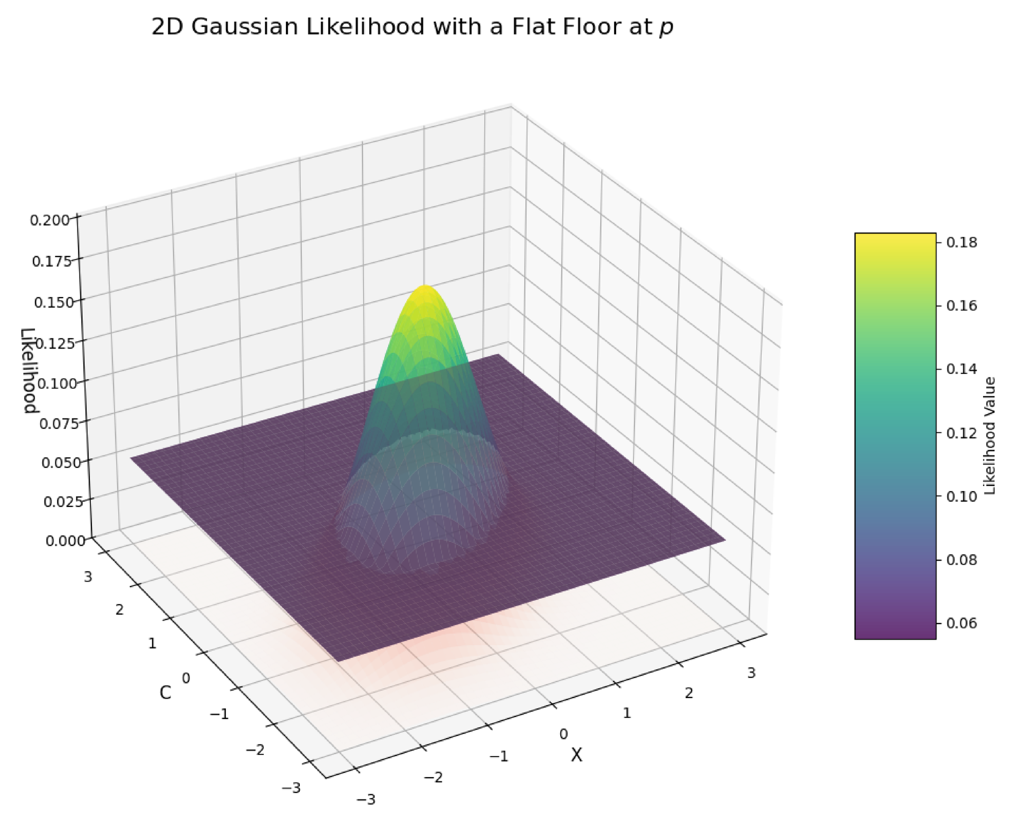
$$\log P(\mathcal{D}|\theta) = \begin{cases} \log \mathcal{L}_i + \log(1-p), & \text{if } \log \mathcal{L}_i + \log(1-p) > \log p - \log \Delta \\ \log p - \log \Delta, & \text{otherwise} \end{cases}$$

Key Insight

We fit for this 'floor' as a free parameter, fully automating the anomaly detection process.

Demo:

github.com/samleeney/Bayesian-Anomaly-Detection/blob/main/demo_anomaly_detection.ipynb



JAX-bandflux

A differentiable framework for supernova analysis:

Key Features:

- GPU-accelerated SALT3 model fitting
- Built on JAX for automatic differentiation
- Integrates with BlackJAX for nested sampling
- Handles large supernova datasets efficiently

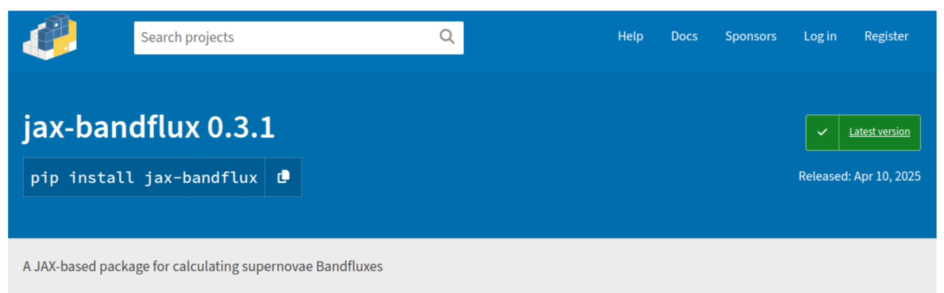
Example: handley-lab.co.uk/nested-sampling-book/physics/supernovae.html

SALT3 Model:

$$F(p, \lambda) = x_0 \left[M_0(p, \lambda) + x_1 M_1(p, \lambda)\right] \times e^{c \times CL(\lambda)}$$

Bandflux Integration:

$$F_{\text{band}} = \int_{\lambda_{\min}}^{\lambda_{\max}} F(p, \lambda) \cdot T(\lambda) \cdot \frac{\lambda}{hc} d\lambda$$

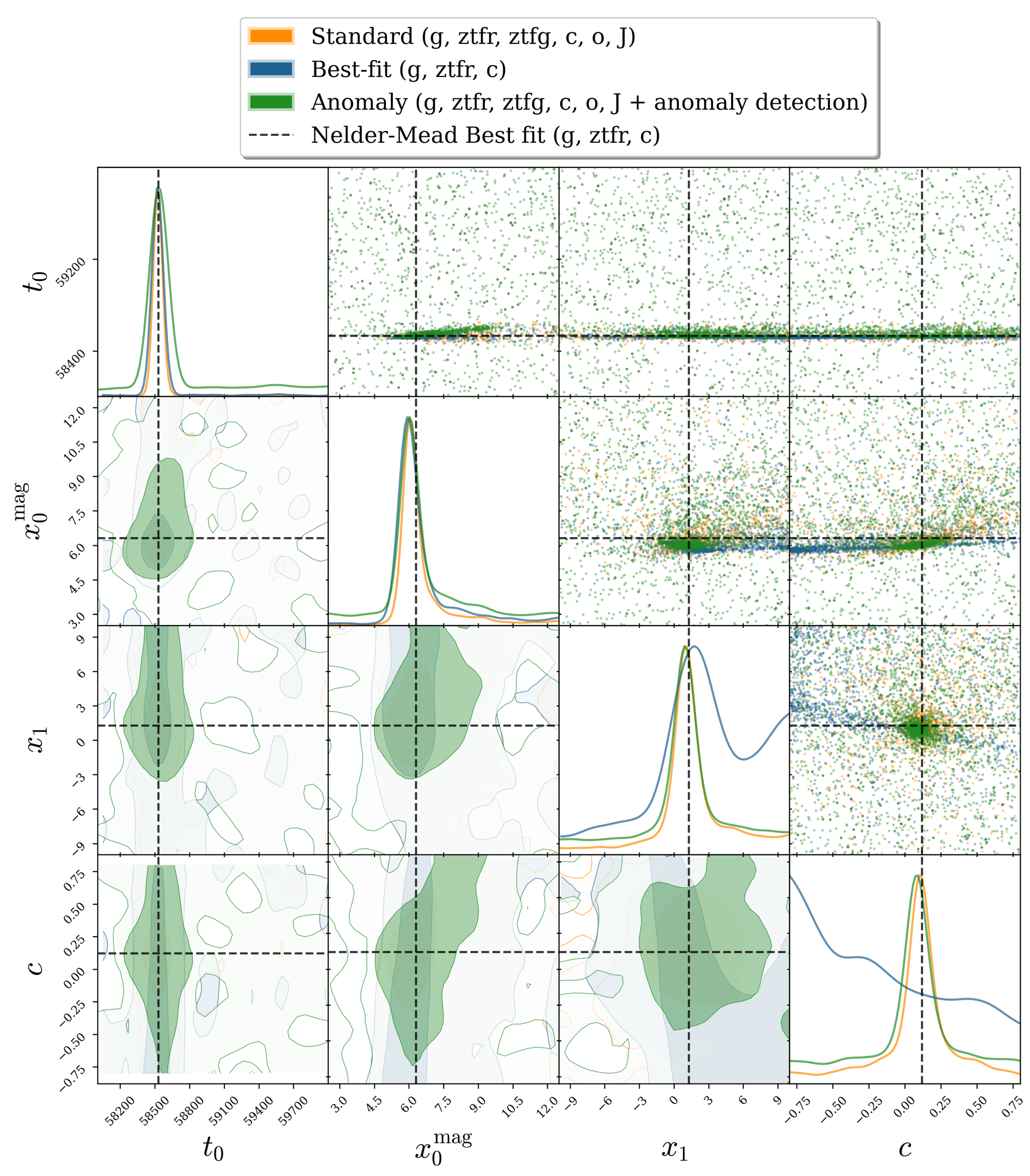


Main Advantages

Utility of Bayesian anomaly detection for Ia analysis:

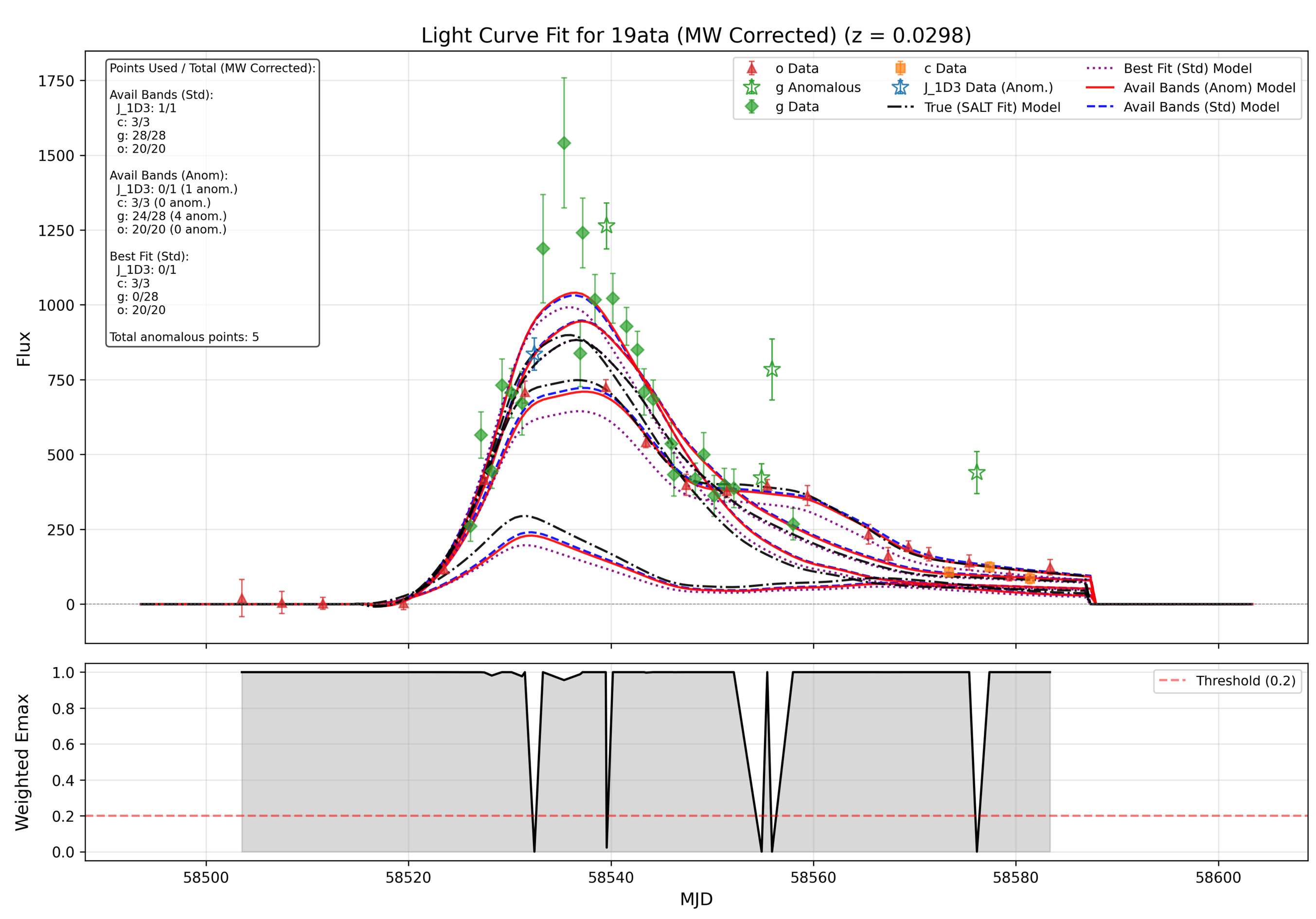
1. Fully automated anomaly detection
2. Fully automated filter selection
3. Preserves previously 'bad' filters by mitigating anomalies

Corner Plot Comparison



Standard SALT (orange) vs. anomaly detection (green) - tighter constraints.

SN 19amo: Light Curve



Data from Do et al. (2025)

Next Steps

Future Applications:

- Extend framework for distance measurements
- Estimate H_0 using robust supernova samples
- Apply to other astronomical datasets

Code: github.com/samleeney

Paper: arXiv:2211.15448